

Covid-19 healthcare facilities: accessibility contrasts in a Brazilian metropolitan city

Unidades de saúde para Covid-19: contrastes de acessibilidade em uma cidade metropolitana brasileira

Instalaciones de salud para Covid-19: contrastes de accesibilidad en una ciudad metropolitana brasileña

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Abstract

The Covid-19 outbreak changed the dynamic in cities around the world. To avoid the collapse in the healthcare system, several cities restricted or forbid people's mobility to diminish the Covid-19 contagion. Meanwhile, a number of researchers developed online initiatives such as websites, apps and chatbots, to inform and guide people about the Covid-19 and its effects. In this paper, we combine data gathered from a dialogue chatbot that indicates healthcare facilities to individuals, with Covid-19 daily reports on new cases and mortality and demographic and socioeconomic factors to carry out analysis on geography and Covid-19 healthcare facilities in a major metropolitan city in Brazil. Results show that less wealthier areas are more populous, report high Covid-19 contagion level and request healthcare facilities locations more often. These findings shed light on Covid-19 healthcare facilities mobility patterns, which is influenced by area features and can be used to design and plan more equitable and accessible cities.

Keywords: Covid-19; Healthcare facilities; Inequality; Data science.

Resumo

O surto de Covid-19 mudou a dinâmica nas cidades ao redor do mundo. Para evitar o colapso do sistema de saúde, muitas cidades restringiram ou proibiram a mobilidade das pessoas para diminuir o contágio da Covid-19. Enquanto isso, vários pesquisadores desenvolveram iniciativas online, como sites, aplicativos e chatbots, para informar e orientar as pessoas sobre o Covid-19 e seus efeitos. Neste artigo, combinamos dados coletados de um chatbot que possui a capacidade de indicar unidades de atendimento de saúde para indivíduos, com relatórios diários de Covid-19 sobre novos casos e mortalidade e fatores demográficos e socioeconômicos para realizar análises geográficas e unidades de saúde de Covid-19 em uma grande metrópole do Brasil. Os resultados mostram que as áreas menos abastadas são mais populosas, relatam alto nível de contágio de Covid-19 e solicitam com mais frequência indicações de unidades de saúde. Essas descobertas lançam luz sobre os padrões de mobilidade das unidades de saúde da Covid-19, que são influenciados pelas características da área e podem ser usados para projetar e planejar cidades mais equitativas e acessíveis.

Palavras-chave: Covid-19; Unidades de saúde; Desigualdade; Data science.

Resumen

El brote de Covid-19 ha cambiado la dinámica en las ciudades de todo el mundo. Para evitar el colapso del sistema de salud, muchas ciudades han restringido o prohibido la movilidad de las personas para reducir el contagio de Covid-19. Mientras tanto, varios investigadores han desarrollado iniciativas en línea como sitios web, aplicaciones y chatbots para informar y educar a las personas sobre el Covid-19 y sus efectos. En este artículo, combinamos datos recopilados de un chatbot que tiene la capacidad de referir centros de atención médica a individuos, con informes diarios de Covid-19 sobre nuevos casos y mortalidad, y factores demográficos y socioeconómicos para realizar análisis geográficos y de centros de atención médica de Covid-19 en una gran metrópoli de Brasil. Los resultados muestran que las zonas menos

acomodadas están más pobladas, reportan un alto nivel de contagio de Covid-19 y solicitan indicaciones más frecuentes a las unidades de salud. Estos hallazgos arrojan luz sobre los patrones de movilidad de los establecimientos de salud de Covid-19, que están influenciados por las características del área y pueden utilizarse para diseñar y planificar ciudades más equitativas y accesibles.

Palabras clave: Covid-19; Establecimientos de salud; Desigualdad; Ciencia de datos.

1. Introduction

Fortaleza is the 5th largest capital in Brazil comprising 2.6 million inhabitants distributed in 121 neighborhoods according to the 2010's Brazilian census¹. The city's economy is organized into three main segments: industry, agriculture and services, which represent 72% of its Gross Domestic Product – GDP. Fortaleza is quite dynamic and attracts tourists worldwide, but the situation has changed since the Covid-19 outbreak.

The Covid-19 is a disease caused by a new coronavirus variant, which was first observed in the city of Wuhan, China, in December 2019. Symptoms generally include fever, dry cough, loss of taste, shortness of breath and in severe cases (which affects on average 5 % of those infected (Lauer et al., 2020)), can reach pneumonia and death. Due to its high contamination degree (Chakraborty & Ghosh, 2020), cases of Covid-19 are observed in several countries (Boulos & Geraghty, 2020). To avoid the collapse in the healthcare systems, cities worldwide restricted or forbid people's mobility to diminish the Covid-19 contagion (Lau et al., 2020). Meanwhile, a number of researchers developed online initiatives to inform and guide people about the Covid-19 and its effects. As an example, in Fortaleza a group of researchers, professors and students created the Dr. Health dialogue chatbot² which helps people to check their health conditions and Covid-19 symptoms and, if demanded, the indication of the nearest healthcare location through geolocation (Gallegos, 2021).

In this paper, we combine data gathered from Dr. Health healthcare facilities indications, with Covid-19 daily reports and demographic and socioeconomic factors from Fortaleza to carry out analysis on geography and Covid-19 healthcare facilities. Specifically, we use the Open Street Map API³ attached to the Dr. Health dialogue chatbot dataset to study individual's position and the nearest Covid-19 healthcare place in Fortaleza. We link Dr. Health dataset containing individual's mobility to the Covid-19 daily reports to map chatbot requests and Covid-19 contagion relationship. Then, we analyze properties of 121 neighborhoods located in Fortaleza by looking at demographic and socioeconomic factors, and combine the outcomes with Dr. Health and Covid-19 daily reports. This allows us to link the Covid-19 contagion and Dr. Health chatbot requests from individuals by neighborhoods in Fortaleza, including demographic and socioeconomic features.

Results show that less wealthier areas are more populous and report higher Covid-19 contagion levels, and healthcare facilities indications are requested more often. In particular, in these areas individuals have more access and shorter travels distances to Covid-19 healthcare facilities, but they spend more time to reach these places. These findings shed light on Covid-19 healthcare facilities mobility patterns, which is influenced by the area features and can be used to design more equitable and accessible cities.

The paper is organized as follows: in Section 2 related works are listed and described. In Section 3 datasets, databases and the methodology applied are described. Then, in Sections 4 the results are detailed and in Section 5 the final considerations are developed.

2. Literature Revision

In the work of Jeon-Young et al. (2020), the authors measure the spatial accessibility of Covid-19 healthcare facilities

¹ Brazilian Institute of Geography and Statistics (<https://www.ibge.gov.br/>)

² <https://digital.fortaleza.ce.gov.br/saude/chatbot-dr-saude>

³ Open Street Map API (<https://www.openstreetmap.org>)

with a particular focus on Illinois, USA. They apply the Enhanced Two-Step Floating Catchment Area (E2SFCA) method through a parallel computing strategy based on Cyber Geographic Information Science and Systems (cyberGIS) to calculate a bed-to-population ratio for each hospital location, and then sum up these ratios for residential locations where hospital locations overlap. Even though this work focuses in just one state, authors compare the spatial accessibility measures for Covid-19 patients to those of population at risk, and identifies which geographic areas need additional healthcare resources to improve access. They delineate the areas that may face a Covid -19-induced shortage of healthcare resources and identify vulnerable population residing in the areas with low spatial accessibility.

Poverty and inequality during the Covid-19 outbreak is studied in Patel et al. (2020). Authors point out that for people of low socioeconomic status, a number of factors increase their exposure to Covid -19: (I) economically disadvantaged people are more likely to live in overcrowded accommodation, (II) financially poorer people are often employed in occupations that do not provide opportunities to work from home, and (III) those in low socioeconomic status groups are more likely to have unstable work conditions and incomes, conditions exacerbated by the responses to Covid -19 and its aftermath. Besides authorities saying that "Covid-19 does not discriminate", this paper suggests the opposite: less wealthier communities are more affected by the Covid-19 pandemic.

A consistent work on chatbots design and application to fight against Covid-19 pandemic is depicted in Miner et al. (2020). In this work, authors describe advantages and drawbacks on how chatbots have been used for health-related purposes, from supporting clinicians with clinical interviews and diagnosis to aiding consumers in self-managing chronic conditions. For instance, chatbots can help at diagnosing diseases but cannot substitute medical doctors for prescribing drugs.

Inspired by these related works but exploring further approaches, we propose to use demographic and socioeconomic factors, combined with Covid-19 contagion and chatbots datasets within a metropolitan city, and link these data with geolocation. Our goal is to characterize differences between Covid-19 healthcare facilities in areas within Fortaleza city, Brazil, with diverse demographic and socioeconomic factors, which may be related to differences at reaching nearby Covid-19 healthcare facilities.

3. Materials and Methods

Socioeconomic and demographic data of Fortaleza are collected from the Brazilian Institute of Geography and Statistics – IBGE website⁴ comprising variables such as population, area, housing, income, education and life expectation. Health facilities data on places apt of caring Covid-19 individuals are obtained from the Fortaleza's official website⁵ and the city neighborhoods boundaries data from the Fortaleza Open Data website⁶.

A partnership between laboratories, universities, and public health department developed the IntegraSUS website⁷: an online platform based on health monitoring and management systems, first released in 2019 for transparency in the public health service. The IntegraSUS is connected to a GitHub repository⁸ from where we collected Covid-19 data from individuals reported as infected or dead in Fortaleza, which are daily updated and freely available.

The Covid-19 encouraged a number of initiatives worldwide to aid people at finding health facilities such as mobile apps, websites and chatbots, the latter being "conversational agents that leverage machine learning and natural language processing to understand intents in order to reply with appropriate answers" (Judson et al., 2020). In Fortaleza, a group of researchers, professors and students developed the Dr. Health conversational chatbot⁹, which is available since mid-April 2020 and help individuals to check their health conditions and symptoms and, if demanded, provide the nearest public health facility

⁴ <https://www.ibge.gov.br/>

⁵ <https://www.ibge.gov.br/>

⁶ Fortaleza Open Data (<https://dados.fortaleza.ce.gov.br/catalogo/dataset/limite-bairros>)

⁷ <https://integrasus.saude.ce.gov.br/>

⁸ <https://github.com/EscolaDeSaudePublica/coronavirusAPI/issues/17>

⁹ <https://drsaudefortaleza.ce.gov.br/>

displayed in an online map based on the individual's request and his current location (Gallegos, 2019). Over the period of 45 days, we collect almost 10k unique interactions between anonymous users and Dr. Health, where a fraction of it is related to healthcare facilities indications containing timestamp, day, lat-long coordinates of each individual's origin and the nearest healthcare facility destination based on the Open Street Map API, and average elapsed time into four different categories: by car, by bus, walking and by bike (bicycle).

The algorithms developed in this work for the analysis are based on the Python Programming language and are implemented using the Google Collaboratory¹⁰ online cloud service that mimics desktop notebooks environments, does not require any configuration and has GPU's availability allowing deep learning and image processing tasks (Bisong, 2019). The Collaboratory has embedded functions and modules that minimize the coding needs with over 137.000 libraries and 198.826 packages (Carneiro et al., 2018).

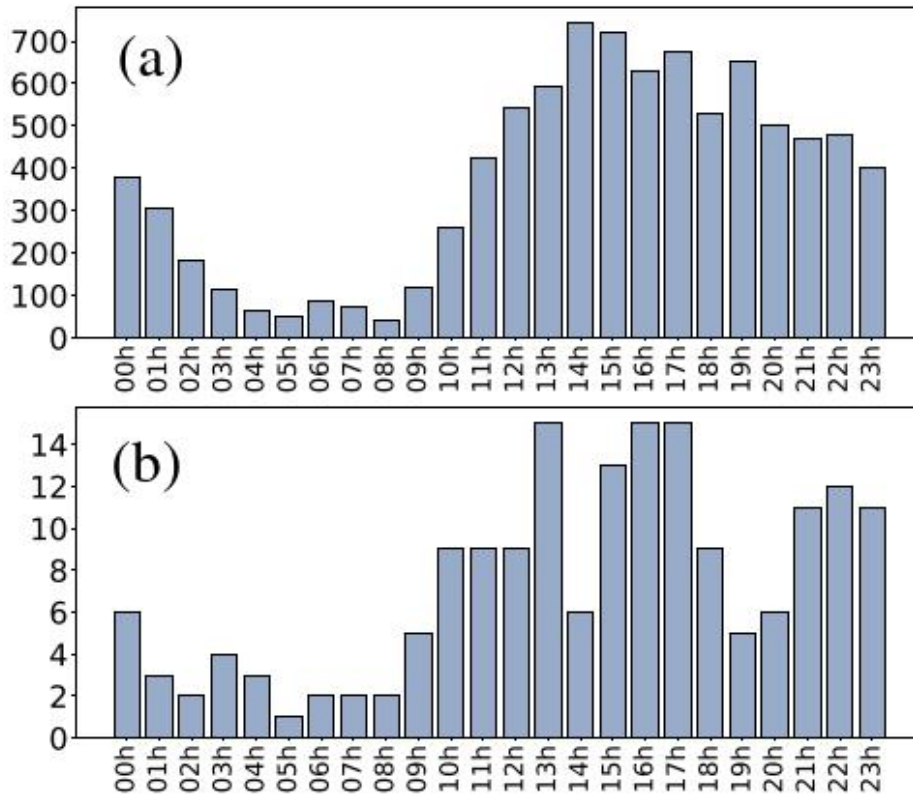
4. Results and Discussion

Fortaleza has 121 neighborhoods and the data collected from IBGE, IntegraSUS and the Dr. Health conversational chatbot are organized by these 121 areas. Our goal focuses on verifying contamination levels, the related user's origin-destination to healthcare facilities, as well as relevant demographic and socioeconomic correlations.

Dr. Health database registers timestamp containing time, year, month and day from each user interaction. Timestamps are formatted using the Python datetime library, where numeric date is converted into days of a week. Similarly, to the days of a week conversion, time is also manipulated to check when Dr. Health is mostly demanded per user and time. Considering the 45-period data collection, in Figure 1 we observe that (a) Dr. Health is mostly demanded in the afternoon until late night and (b) from hour 10 and 24 for users that demanded healthcare indication.

¹⁰ <https://research.google.com/colaboratory/>

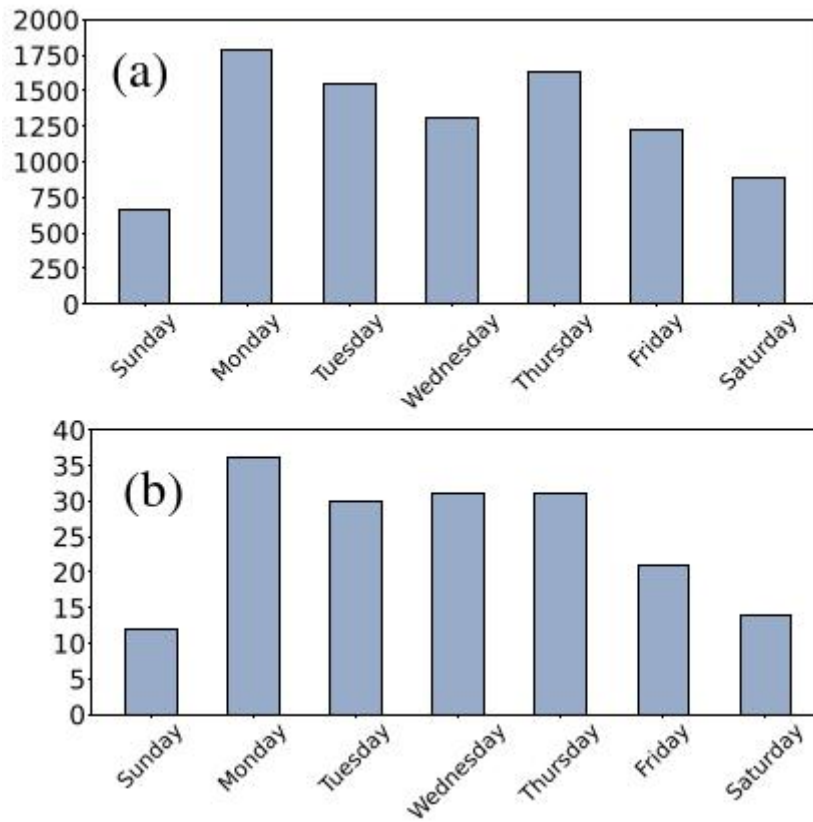
Figure 1: Dr. Health conversation per time. (a) Bar plot shows conversations of all users, while (b) bar plot represent the fraction that demands the nearest healthcare indication.



Source: Authors.

We analyze the chatbot's database to verify when it is mostly used: weekdays or weekends. The Figure 2 depicts picks of use during weekdays rather than weekends, occurring in the set with healthcare indications (b) and the entire number of users (a). From this result, one can speculate the reasons of this outcome which might happen due to different policy restrictions (quarantines and lockdowns) or even to individual's lifestyle during weekdays and weekends (Bwire, 2020; Gomes et al., 2020).

Figure 2: Dr. Health conversation per day. Users chat with the chatbot mostly during weekdays than weekends both on the set of individuals who nearest healthcare indications (b) and the entire number of users (a).



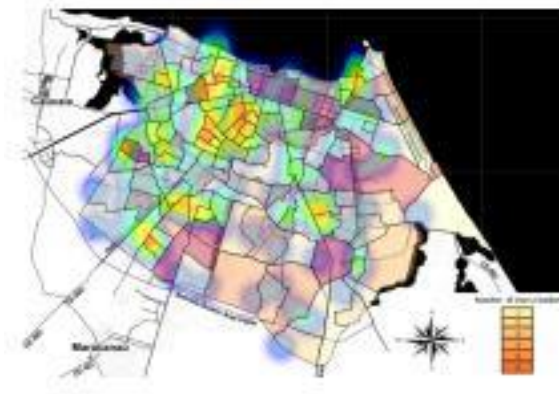
Source: Authors.

A correlation analysis considering the 121 neighborhoods in Fortaleza between Dr. Health data, Covid-19 contamination, healthcare places, demographic and socioeconomic variables is also performed. We find a correlation of 0.59 ($p \leq 0.05$) between Covid-19 contamination and population, and 0.46 ($p \leq 0.05$) between population and Dr. Health healthcare indications data per user, by neighborhood. We also find correlation between Covid-19 contamination and Dr. Health healthcare indications data per user, by neighborhood, of 0.44 ($p \leq 0.05$). These results show that more populated neighborhoods are the mostly contaminated, and coincidentally are the areas where individuals usually request the healthcare facilities indications from the dialogue chatbot.

The Figure 3 shows Fortaleza and its neighborhoods, and a heat map layer grouping two variables: most affected areas by Covid-19, and areas that individuals most use Dr. Health chatbot. Note that the more reddened is the areas, the greater the ratio of individuals infected by Covid-19 and, consequently, the conversational chatbot is more demanded as well. This result allows us to observe that areas most affected by the Covid-19 epidemic are basically the same areas that usually requests information and healthcare facilities guidance from individuals. Note also that most Covid-19 affected areas are located at the coastal zone (northwest region) and the west zone, which is similar as reported by the Fortaleza city hall¹¹. South and east zones have sparse affected areas and thus the chatbot demand is lower.

¹¹ <https://g1.globo.com/ce/ceara/noticia/2020/07/31/meireles-aldeota-e-messejana-tem-maior-numero-de-casos-de-covid-19-em-fortaleza-veja-situacao-nosbairros.ghtml>

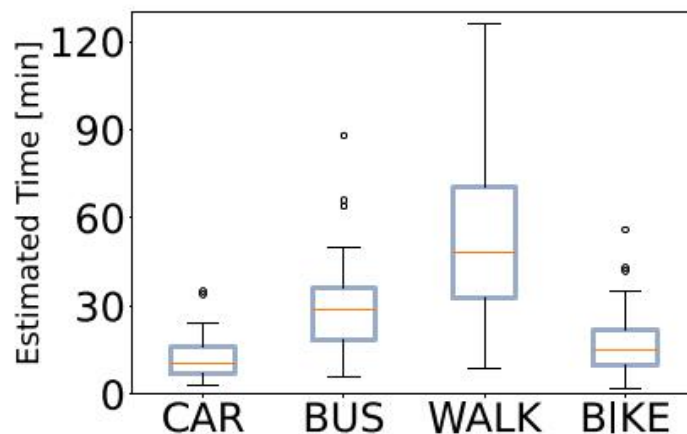
Figure 3: Fortaleza and its 121 neighborhood areas with a heat map layer grouping two variables: most affected by Covid-19, and where individuals most use Dr. Health dialogue chatbot.



Source: Authors.

The Open Street Map API allow us to estimate travel time in minutes between the user location and the nearest healthcare facility, by chatting with Dr. Health chatbot. The nearest path is calculated through streets and avenues as depicted in Figure 4 into four categories: by car, by bus, walking and by bike. Fortaleza streets are narrow and usually have heavy traffic jams between early morning and the evening, which reflects the median estimate travel time expended by cars (14 minutes), buses (30 minutes), and bikes (18 minutes): for short travels and poor areas located at northwest, west and east, bikes are preferred than buses; in richer areas located at the north and center, cars are preferred.

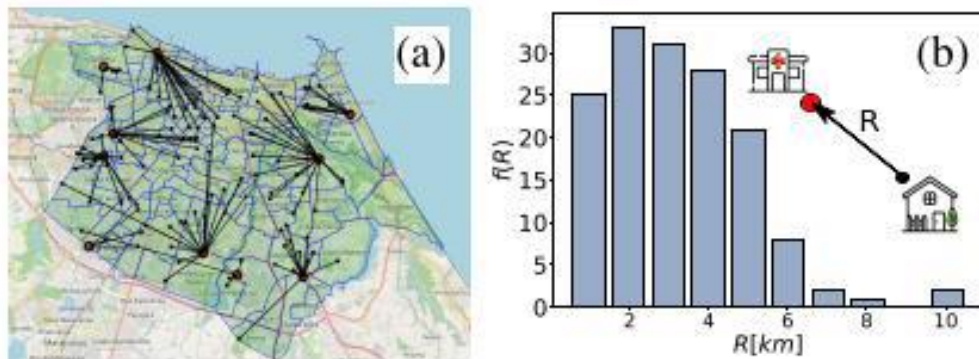
Figure 4: Estimate travel time in minutes between the user location and the nearest healthcare place into four categories: car, bus, walking, and bike (bicycle).



Source: Authors.

The estimated travel distance of an individual and the nearest healthcare facility is shown in Figure 5(a) from Dr. Health chatbot dataset, calculated using the Open Street Maps API. Results show that healthcare facilities with greater demand are usually located in less wealthy and nearby individuals when compared to richer areas, a result the has no similarly in previous works published about Brazil and worldwide (Pereira, 2021; Tanne, 2020; Kirby, 2008). Perhaps, this situation encouraged individuals in poor areas to chat more frequently with Dr. Health, which demonstrates the increase use of chatbots in a variety of situation (Adamopoulou & Moussiades, 2020; Dahiya, 2017).

Figure 5: (a) Estimated travel distance from an individual and the nearest healthcare facility. Demanded healthcare places are usually located in less wealthier and closer from individuals (northwest, west and east sites), when compared to richer areas (north and east sites). The (b) Radial distribution $f(r)$ between the location of users and the nearest healthcare place shows that healthcare places are the travel expended by users correspond to a small portion of the city's average radius.



Source: Authors.

Finally, we analyzed the radial distances “ R ” between the most frequent users’ call points and their respective nearest Covid-19 healthcare facilities indications. In Figure 5(b) a histogram of R of all requested travels is presented. On average $R \approx 2.5$ km on travel distance travelled by users corresponding to a small portion of the city’s average commuting radius ($R_{city} \approx 10$ km) indicating that there are, in this sense, population areas grouped with healthcare facilities that can be characterized as metapopulations sets (i.e., population in which individuals are spatially distributed in a habitat into two or more subpopulations) (Arenas et al., 2020). In addition, the behavior of R works as a proxy for characterizing the visitor density profile around a region and may, with appropriate approximations, be used as origin-destination relationships, which is fundamental to the diffusion process for any disease among metapopulations. We believe that once Dr. Health dialogue chatbot becomes more popular, it should be possible to use its dataset as a Covid-19 tracking tool among such metapopulations (Schlapfer, 2021).

Based on the above results on travel and time distances in this paper, one can speculate whether Covid-19 contamination data depends on other demographic and socioeconomic independent factors. Outcomes highlight the following coefficients, standard errors and p-values (** for $P \leq 0.01$, and *** for $P \leq 0.001$) for independent factors, respectively: Dr. Health interactions $6.5(2.1)***$, life expectation $114.86(43.85)**$, and income $282.60(66.61)***$. About 84.56% of the variations with Covid-19 contamination as dependent variable is explained by changes in Dr. Health chatbot interactions, life expectation and income as independent variables, by neighborhood. These results show that income and life expectation are related to Covid-19 contagion, and the importance on the Dr. Health interactions data as an independent variable is explained by its relation with Covid-19 contagion data.

5. Final Considerations

In this paper, we combined data gathered from Dr. Health chatbot comprising healthcare facilities indications, Covid-19 daily reports on new cases and mortality, and demographics and socioeconomic factors from a Brazilian metropolitan city (Fortaleza, in Brazil) to carry out -analysis on geography and Covid-19 healthcare locations. The Open Street Map API attached to the Dr. Health dialogue chatbot dataset allowed us to study individual’s position and their respective nearest Covid-19 healthcare place in Fortaleza, which was later related to Covid-19 daily reports to map chatbot requests and Covid-19 contagion relationship. The features regarding the 121 neighborhoods located in Fortaleza were also analyzed by grouping demographic and socioeconomic factors, and Dr. Health chatbot healthcare facilities indications to Covid-19 daily reports.

Results show that less wealthier areas report high Covid-19 contagion levels and request Dr. Health chatbot more often,

including cases where the nearest Covid-19 healthcare place is also demanded. Usually, areas where individuals are less wealthy demand more time to commute to Covid-19 healthcare facilities due to the mobility options (bikes or buses), with greater distances and more time spent. In contrast, although wealthier individuals are further away from Covid-19 healthcare facilities in Fortaleza, they reach these places faster.

This paper has some limitations: Dr. Health dialogue chatbot dataset was limited to 45 days and the IntegraSUS data from individuals reported as infected or dead may be outdated due to update delays. Also, our analysis is limited to the Fortaleza city although it may reflect other tropical developing cities in countries worldwide. Even with these caveats, however the data collections, analysis and findings shed light on Covid-19 healthcare facilities mobility.

Future works should consider to include people's sociability within and between areas, commuting preferences, as well as internet accessibility, for studying mobility patterns and best positioning healthcare facilities for Covid-19 in tropical cities. Finally, for research purposes we suggest the application of the ideas described in this paper to other tropical cities worldwide. We hope the findings described in this paper help researchers and policy makers in designing equitable and accessible cities.

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